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# Non-performing exposures prevention in Millennium BCP

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## Abstract

This paper explores the determinants of clients become non-performing. Since the 2008 financial crisis, several member states have been suffering from high levels of non-performing loans, which ultimately has a negative impact on the economies. As a result, ECB and EBA defined strict policies to reduce non-performing loans ratio. Millennium BCP is one of the banks targeted by these policies and, therefore, is trying to implement a factors' model to prevent clients from becoming non-performing. To perceive whether or not it holds in practice, the model was back tested using a logit model.



**Key words:** clients, non-performing exposure, trigger and probability

## Index

## 1. Goals of the research project

The objectives of the internship was to support the development and back test the model BCP is trying to implement to identify and manage potential non-performing clients at a very early stage. These clients can be identified through a set of triggers that will be further explained; the verification of one of the criteria might lead to a plan's execution in order to protect the bank from potential losses. The back-testing procedure aims to verify whether the chosen criteria have impact on being classified as an NPE, thus if these factors could increase the probability of default.

According to the ECB, several banks in Member States across the Euro Area are currently suffering from high levels of non-performing loans[1] (NPLs). In their view, given the balance sheet, profitability, and capital constraints faced by banks with high NPL levels, high NPL levels have a negative impact on bank lending to the economy. Therefore, increasing asset quality is one of the priorities established by the European Central Bank.

ECB began to focus on this problem by 2014 and since then has been intensifying its supervisory work on NPLs. As a result, it developed a "Guidance to Banks on non-performing loans" that banks must follow. This guidance is applicable to all banks supervised directly under the Single Supervisory Mechanism[2] (SSM), including their international subsidiaries.

Through Graph 1 and 2, it can be observed that ratios of non-performing loans and impaired loan ratios have been significantly higher for banks based on the countries most affected by the financial crisis. As such, it comes as no surprise that Millennium, based in Portugal, is one of

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[1] In accordance with the ECB, "a bank loan is considered non-performing when more than 90 days pass without the borrower paying the agreed instalments or interest".
[2] The Single Supervisory Mechanism refers to the system of banking supervision in Europe.

the banks targeted by the guidance aforementioned and it is currently under the supervision of the ECB banking supervision.

Despite NPLs being the term used, the guidelines developed by the ECB addresses all non-performing exposures (NPEs), following the European Banking Association (EBA) definition. The term NPL is based on several definitions and to overcome the resultant issues EBA presented a single definition of non-performing exposure (NPE). According to paragraph 145 of Annex V of the EBA ITS on supervisory reporting, "non-performing exposures are those that satisfy either or both of the following criteria:

1. Material exposures which are more than 90 days past-due;
2. The debtor is assessed as unlikely to pay its credit obligations in full without realisation of collateral, regardless of the existence of any past-due amount or of the number of days past due."

According to the ECB, this definition is based on two criteria: "past due" and "unlikely-to-pay".

The past due criterion establishes that an exposure cannot be considered past due unless there was a legal obligation to make a payment and payment is compulsory. In the event that none of these requirements are met, non-payment does not constitute a breach. Moreover, as soon as the legal obligation for a mandatory payment has been defined, the counting of days past due begins once any material amount of principal, interest or fee has not been paid at the date it was due.

On the other hand, the unlikely-to-pay criterion relies less on quantitative criteria and gives rise to subjectivity, thus each bank must have clearly defined internal criteria to identify indicators of unlikeliness to pay. Furthermore, it is also important to note that all exposures, even those fully collateralised, should be classified as non-performing if there is an unlikely-to-pay situation.

After having explained what triggered this recent ECB developments, we should now focus on why is this important to Millennium. Firstly, we need to take into account that the bank is under supervision of the ECB banking supervision and therefore needs to comply with these regulatory requirements. Furthermore, it is important to note that the EBA announced, in the beginning of 2018, a five percent NPE ratio[3] threshold; institutions exceeding this amount should apply a recovery strategy in their portfolio. In particular, Millennium had an NPE ratio of 15% in December 2017, which is three times higher than the minimum required. Consequently, it is of paramount importance for the bank to sustainably reduce its levels of non-performing exposures. Such fact justifies the need of the model that is being implemented.

## 2. Literature Review

Several theoreticians have been studying the prediction of corporate bankruptcy. Even though they studied the same subject, the literature produced differs in the choice of variables and in the methodology implemented to predict the probability of bankruptcy. Altman (1968) and Ohlson (1980) developed their own measures of financial distress: Altman's Z-score and Ohlson's O-score, respectively. Both measures were based on accounting variables, however different methodologies were used to estimate the likelihood of bankruptcy. On one hand, the Z-score model was developed using a multiple discriminant analysis (MDA). Altman's model is a linear analysis that incorporates five measures, each one weighted, and if summed up we achieve an overall score that enables us to classify an observation as a distressed or a non-distressed firm. A company with a Z-score below 1.8 is indicative of pending bankruptcy, whereas an enterprise with a Z-score above 3 indicates that it is not probable to go bankrupt. On the other hand, Ohlson (1980) used a logit model to estimate corporate bankruptcy.

[3] According to the EBA definition, Non-performing debt securities and loans and advances / Total gross debt securities and loans and advances.

Moreover, Ohlson (1980) uses nine variables instead of five to develop its model. If the O-score is greater than 3.8%, the firm is likely to go bankrupt.

Like Ohlson (1980), Shumway (2001) used a logit model to predict bankruptcy. Nevertheless, he developed a hazard model for forecasting bankruptcy instead of using a static model as his predecessors. In his model, Shumway (2001) incorporated several market variables previously neglected such as firm's market size, its past stock returns and the idiosyncratic standard deviation of its stock returns. In addition to this, he found that several accounting ratios previously used were poor predictors and it was able to build an accurate model to estimate the likelihood of bankruptcy by combining the aforementioned market variables and two accounting ratios (net income to total assets ratio and total liabilities to total assets ratio).

Following Shumway (2001) procedure, Chava and Jarrow (2004) extended the bankruptcy database and developed two different models able to estimate corporate bankruptcy at a monthly level: a private firm model, using only accounting variables, and a public firm model, using both accounting and market variables. Chava and Jarrow (2004) were able to conclude that the forecasting ability of the models improve significantly using monthly observations instead of yearly ones.

Beaver, McNichols and Rhie (2005) studied the ability of financial ratios to predict bankruptcy. They found some deterioration regarding financial statement ratios' usefulness to estimate bankruptcy; however, improvements in the market-based ratios' ability to predict bankruptcy seem to offset this deterioration. Following this context, Campbell (2008) was able to combine Shumway (2001) and Chava and Jarrow (2004) procedures and extend the previous literature by augmenting the set of explanatory variables and transform some of them. He used monthly data like Chava and Jarrow (2004) and estimated the likelihood of bankruptcy over the next year as Shumway (2001) did. Campbell's (2008) new model, besides the market variables used by Shumway (2001), uses the same accounting ratios as his predecessors but substitutes the book value of assets by their market value and incorporates three new variables: company's cash and short-term assets to market value of assets ratio, market-to-book ratio and the log price per share of the firm.

A client being classified as an NPE can be considered as a proxy for predicting bankruptcy. As a result, the same methodology implemented by the literature abovementioned can be used to back test the model BCP is trying to implement. Therefore, a logit model to predict NPEs over the next period will be used to test our model.

## 3. Model Description

### 3.1. Universe and data treatment

Before going deeper into the model, it is important to clarify to whom does the model apply within the bank clients' database. Firstly, it should be highlighted that the model it is only applicable to clients without credit overdue in the analysis moment, i.e., clients that in the review moment are able to meet their obligations. In addition to this, for the purpose of this model, data is periodically reviewed on a monthly basis and its treatment is developed on a client basis, not on a corporate group one. Secondly, only firms or self-employed entrepreneurs from Corporates and SMEs networks are subject to the model; Corporate and SMEs networks includes every client that has an annual turnover greater than or equal to 2.5 million euros, total credit exposure and exports greater than or equal to one million euros. Furthermore, it was established a materiality level, in which only clients with credit exposure in Millennium BCP greater than 25000 euros are considered.

## 3.2. Triggers

As aforementioned, each bank is required to define its internal criteria. After studying several hypotheses, BCP considered the following factors:

1. Credit rating[4] deterioration of, at least, two notches; final rating is required to be greater than or equal to 10.
    a. Justification: this trigger was taken into account given that asset quality is considered to be low for clients that have grade higher than 9. Therefore, enterprises verifying this criterion have a higher probability of becoming non-performing.
2. New records, in the last two consecutive months, of credit overdue amount superior to 25000 euros in Other Credit Institutions (OCI) reported on Banco de Portugal's Central Credit Register[5] (CCR) as first account holder.
    a. Justification: this factor was considered since it is probable that a client that has credit overdue in OCI does not meet its obligations with our bank.
3. Unjustified returned cheques in the last 90 days before the review.
    a. Justification: returned cheques can be justified or unjustified; if the counterparty receives the amount due, then the cheque is justified, otherwise it is unjustified, unveiling that the client cannot pay the amount due. As a result, such criterion might indicate that the enterprise cannot afford its contractual obligations.
4. Increase of actual credit's share over ten percentage points in clients with credit rating greater than or equal to 10, because of a reduction of the indebtedness level in OCI; minimum initial quota required $\geq$10%.

[4] Credit rating varies between 1 and 15, in which 1 is the best grade and 15 is worst.
[5] "The Central Credit Register CCR contains information on actual credit liabilities of natural or legal persons *vis-à-vis* the entities registered in the CCR".

    a. Justification: if an enterprise has been reducing its actual credit in OCI while keeping the amount due in BCP, the bank can be left behind and end up with an impairment given the quality of the client.

5. Augment of actual credit in the financial system (BCP + OCI) higher than twenty percent in clients that possess a credit rating greater than or equal to 10 and credit exposure in BCP greater than 100000 euros; not applicable to companies with establishment date inferior to three years.
    a. Justification: this factor aims to detect corporations that have low asset quality, and therefore do not have much clearance to enter into new debt agreements, decreasing the probability of the bank receiving the amount due. Moreover, the criterion does not apply to early stage companies since these frequently have a low rating grade and usually increase their indebtedness level during the first years.
6. Record of three collection events in the last three months; breach minimum amount and actual credit in BCP superior to 5000 euros and 100000 euros, respectively.
    a. Justification: if a client had past due credit in the last months, there is a chance that this enterprise does not fulfil its obligations in the near future.
7. Client incorporates a corporate group in which one of the members is in default (credit rating equal to 15).
    a. Justification: a contagion effect might happen, i.e., the fact that one member of the group is in default might influence negatively the client under analysis.
8. Client with credit exposure but without financial statements actualized for more than two years.
    a. Justification: if a firm does not deliver its financial statements from past years, it might indicate that something is not adding up.

9. Credit Division manually inserts a preventive lead[6].
    a. Justification: the risk manager believes the client's financial and economical conditions need to be reviewed in the near future.
10. Clients that the Credit Division decided to keep a high-risk warning after the conclusion of the prevention plan by the bank branch; analysis done by the Credit Division in the end of the quarantine period (6 months).

## 3.3. Model Circuit

In order to implement the model in the bank's system, a circuit grounded on the factors aforementioned is required. The circuit begins with a generation of leads, which can be generated automatically or manually. The leads could have been manually inserted in the system by the Credit Division – trigger 9 - if the risk manager from this division believes, for example, that the client's financial conditions need to be analysed. On the other hand, if the leads have been generated automatically, the generation process does not depend on the risk manager but, instead, it is based on the triggers; the client is just required to verify one of the factors pre-defined.

Having the leads generated, the risk manager from the Credit Division would proceed to the analysis of the enterprise situation and decide whether or not it justifies a plan or the branch bank's intervention. If not, the lead is closed, indicating the motive for the closure; possible motives for the closure of the lead would be operating error, extremely low risk, client with a collection event in motion. Whereas if the risk manager believes an intervention is required, he evaluates the severity of the warning and classifies it as "low-risk" or "high-risk". In both cases, the warning goes to the system, with indication of the motive.

[6] Lead is an action generated in the bank's system.

Nevertheless, if the risk manager classifies the alert as high-risk, an action plan and the timing to execute it is defined, instead of merely informing the branch bank as it would in the case a low-risk alert had been issued. The action plan can be implemented by the Operations Division or by the responsible branch bank. If the action is completed by the first one, the Operations Division would validate whether the loan collaterals are in accordance with the expected by the division responsible for the credit and classify the process as "in agreement" or "in disagreement". While if the action is developed by the latter, the branch bank would execute the tasks defined by the Credit Division; these could include review credit limits, strengthen collaterals, propose a debt restructuring or searching capital assets.

Once the timing to execute the plan runs out, the Credit Division is required to assess whether or not the plan has been carried out by the competent areas. If the plan has been implemented, the risk manager would close it, indicating the motive for the closure, and decide about the severity of the alert; the alert could be maintained as "high-risk" or changed to "watch list". On the other hand, if the plan has not been completed, the risk manager needs to reclassify the warning and indicate which actions are required to be taken. These actions could be, for example, temporarily removal of decision power from branch bank in what concerns to new credit operations, request the Rating Division to reassess the credit rating, suspend the use of lines of credit, anticipate credit limits' review data, temporarily reduction of payment methods' limits (cheques, credit cards) or transfer the client to the Recovery Units. Regardless of the plan being carried out, the warning goes to the bank's system and the client stays in quarantine in what concerns to the generation of new leads in the following six months.

### 3.4. Model Timings

Having the model circuit dissected, we should now focus on the timings that each competent party has to present its work. Firstly, it is important to note that the counting of days is done on working days. Once a lead is generated, the Credit Division has six days to analyse it, decide whether the branch bank's intervention is required and eventually define the type of warning and a plan to be executed. If during this period nothing is decided, then the lead re-enters in the system and the process begins until it is taken care of. On the other hand, if the risk manager decides, there are three possible outcomes:

1. the lead is closed without the participation of the branch bank;
2. a quarantine period is established by the Credit Division so that the risk manager has a better judgement of the facts – maximum quarantine period is 30 days. At the end of this period, the risk manager has six days to decide whether the lead needs to be closed or if a plan of action needs to be implemented. Once again, if he did not make any decision during the period established, the lead is re-inserted in the system.
3. the risk manager classifies the warning and defines the plan of action to be executed in 30 days by the Operations Division or by the responsible branch bank; the area in charge of the plan's execution can negotiate with the Credit Division a 15 days prorogation to extend the plan's deadline. While the plan is being executed, the generation of new leads is suspended.

Once the period defined to execute the plan ends, the Credit Division needs to evaluate whether the proposed actions have been completed, review the alert defined and establish the future course of action; this analysis lasts for eight days. Nonetheless, a quarantine period could be applied to better assess the plan's results; the maximum period is 180 days and at the end of it the risk manager reviews the client's situation and could propose further measures to be implemented.

### 3.5. Warning Rules

As above mentioned, there are three types of warnings: low-risk warning, high-risk warning or watch list; the responsible branch bank can, at any moment, request the warning to be removed or reviewed, regardless of the plan status. In what concerns to the low-risk warning, it remains active for two months and it is monthly reviewed. If in the new analysis the trigger activated is the one that has been activated in the last review, no lead is generated to the Credit Division and the warning is kept in the system. Whereas if the criterion verified is different, a new lead is generated, and the Credit Division must analyse the client under the scope of the circuit defined.

Regarding the high-risk warning, this requires the Credit Division to define a plan of action to be executed by the Operations Division or the responsible branch bank. After being attributed, the alert remains active for six months, without generating new leads in the course of time the plan is being executed. At the end of this period, the high-risk warning is maintained in the system and generates a lead to be analysed by the Credit Division – trigger 10. It is also important to highlight that if the client has a high-risk warning registered in the system, with a plan of action implemented by the branch bank and validated by the Credit Division, and it enters in default, the alert must continue to be in the system.

In what concerns to the watch list alert, this is automatically removed from the system six months after and the client can re-enter in the lead's circuit to be analysed if any trigger is activated.

## 4. Empirical Analysis

### 4.1. Technique used to analyze the problem

As the model that BCP is trying to implement is composed by dummy variables, a non-linear probability model, such as logit or probit, would be required to test whether or not the model holds on practice. Actually, using linear probability models with binary variables has several disadvantages. Firstly, it places no restrictions on the parameters β, thus if the OLS estimates $\hat{\beta}$

are used to compute the estimated probabilities, we might obtain probabilities smaller than zero or larger than one, in which case they are not real probabilities:

$$y_i = x_i'\beta + \varepsilon_i , E[\varepsilon_i] = 0 \text{ (linear probability model)}$$

as $E[\varepsilon_i] = 0$ and $y_i$ can take only the values zero and one, it follows that

$$x_i'\beta = E[y_i] = 0 * P[y_i = 0] + 1 * P[y_i = 1] = P[y_i = 1] = E[y_i] = x_i{}'\beta$$

On the contrary, non-linear models for probabilities require that 0≤xi'β≤1. Secondly, the $\varepsilon_i$ are not normally distributed given that the variable $y_i$ can take only values zero and one, such that $\varepsilon_i$ is random variable with a discrete distribution:

$$\varepsilon_i = 1 - x_i{}'\beta \text{ , with probability xi'β}$$

$$\varepsilon_i = -x_i{}'\beta\text{, with probability 1 – xi'β.}$$

As a result, the conventional OLS formulas for the standard errors do not apply.

Probit and logit models only differ on the choice of the distribution; probit uses the normal distribution, whereas logit uses the logistic one. In this case, the logistic distribution was the one that has been chosen.

### 4.2. Data Description

In order to estimate a logit model, we need an indicator of NPE and a set of explanatory variables. The NPE indicator is taken from BCP clients' database. The indicator equals one if the client started being classified as an NPE in 2018 and zero otherwise; in particular, if the client has never been marked as an NPE the indicator is zero.

To evaluate whether or not the new model being implemented by the bank holds in practice, Trigger 1, Trigger 2, Trigger 4 and Trigger 5 were considered as independent variables - the remaining triggers could not be part of the model due to data constraints. In order to construct the explanatory variables, some adjustments to the raw data (BCP clients' database) were done. Firstly, even though the model only encompasses firms or self-employed entrepreneurs from Corporates and SMEs networks, the analysis was extended to the small companies or self-employed entrepreneurs from Retail networks in order to have a broadened analysis. In addition to this, for the purpose of this analysis only clients that had record of credit rating and actual credit in the entire financial system (BCP + OCI) were considered. Secondly, the data retrieved is segregated in four moments over 2017: January to March, February to May, January to July and January to December. Such division gives us the evolution of the clients' financial and economic conditions over 2017 in 2 months, 3 months, 6 months and 12 months. The independent variables, likewise the dependent variable, give us a binary response; if the client accomplishes the criterion defined, the outcome is one, and zero otherwise.

### 4.3. Empirical Results

Table 1 summarizes how many times each trigger was activated and how many times at least one criterion was realized in each time interval, both in absolute terms and in relative terms to the number of clients. Table 1 is divided into three Panels, A, B and C, and each panel is segregated in two sections; Section 1 describes how many times each trigger was activated, the total number of times at least one trigger was activated and the number of clients, whereas Section 2 shows us the probability of each factor being verified and gives us the probability of at least one factor being accomplished. Panel A in Table 1 outlines the distribution of the triggers for the entire data set, Panel B in Table 1 describes only for the clients classified as NPE in 2018 and Panel C in Table 1 illustrates just the non-NPE cases.

Regarding Panel A, it can be stated that the results for the entire data set are not much significant relative to the number of clients, given that the probability of at least one trigger being activated is between 4% and 9% for the entire observations. In addition to this, trigger 1 is the most verified, accounting for more than 50% of the cases in which the factors were activated (e.g. if the number of months under analysis is two, the probability of the first explanatory variable's criterion being accomplished is 2.3% vs. the probability of at least one factor being realized is 4.3%). Moreover, the number of triggers verified increase as time span is broadened, except from trigger 2, which would be expectable as we are working with clients' economic and financial conditions and these are not expected to be deteriorated in such a short time period.

In what concerns to Panel B, results are more significant given that there is at least a 15.2% probability of verifying one of the triggers tested, which goes in line with the expected since this kind of clients have their situation deteriorated. Moreover, if we consider the longest period under analysis, 12 months, there is almost a 40% probability of any factor being activated; this being said, about two-fifths of the clients classified as an NPE in 2018 accomplished one of the criteria in the previous year. Despite the probability of the model detecting this kind of clients being higher, one should bear in mind that 60% of the cases that are classified as an NPE in 2018 would not be detected by the model considering the previous year's evolution of the economic and financial conditions. As before, trigger one is the most common one within the sample, followed by trigger 2, and as time span increases results show more significance.

Given that the number of clients classified as NPE accounts for less than 5% of the observations, Panel C shows similar results to Panel A; triggers do not have an important impact, apart from trigger 2 as interval periods being used increase the number of factors verified augments and trigger 1 is the factor most verified. Despite the similarities between the Panels A and C, it can be argued that, for each factor and each interval period, there is a probability more than three times higher of an NPE verifying one of the triggers than a client not classified as an NPE (e.g. probability of an NPE over a two-month period accomplishes criterion 1 equals 7.1% vs. probability of a non-NPE over the same period equals 2.3%) – Table

2. Nevertheless, for the twelve-month period, one could interpret that the absolute number of false positives detected by the model is quite high – 4057 in 48923 clients.

Despite Table 1 showing that Clients classified as NPE have more significance than the remaining sample, it is not clear how useful are these variables in predicting NPEs. Therefore, we now estimate the probabilities of being an NPE over the next period using a logit model.

We assume that the marginal probability of being an NPE over the next period follows a normal distribution and is given by

$$P_{t-1}[y_{it} = 1] = \frac{1}{1+e^{-\left(\alpha+\beta x_{i,t-1}\right)}} ,$$

where $y_{it}$ is an indicator that equals one if the client is classified as an NPE in 2018, and $x_{i,t-1}$ is a vector of explanatory variables known at the end of the chosen time period in 2017. A higher level of $\alpha + \beta x_{i,t-1}$ implies a higher probability of being an NPE in 2018.

Table 3 reports logit regression results for various alternative time period and specifications. In what concerns to the two-month period, two models are presented given that the model is not statistically significant; Model I includes the four explanatory variables aforementioned (Trigger 1, Trigger 2, Trigger 4, Trigger 5), whereas Model II does not take into account Trigger 4. For the remaining periods, only Model I was considered.

Regarding the two-month horizon, as can be observed through Model I in Table 3, apart from Trigger 4, all the explanatory variables are statistically significant at a 5% significance level and with a positive coefficient. Since Trigger 4 is not statistically significant at this level, Model II considers the same number of observations but excluding this variable. In this case, all independent variables are statistically significant at the chosen level and with a positive coefficient. To test the significance of Model I, a likelihood ratio test was performed:

$$LR = -2 \ln\left(\frac{L_R}{L_U}\right) ,$$

$L_R$ is the likelihood of the restricted model, Model II, and $L_U$ is the likelihood of the unrestricted model, Model I. This test confirms the idea that Model II is a better choice over Model I taking into account that P-value is higher than 5% - Table 3.

In what concerns to the remaining periods, the conclusions retrieved are slightly different from the previous analysis. Firstly, for the three-month, sixth-month and twelve-month periods, all explanatory variables are statistically significant at a 5% significance level and with a positive coefficient. Therefore, as can be seen through the likelihood ratio test, Model I is statistically significant.

In order to evaluate the effect that each factor has on average in the probability of a client being classified as an NPE, average marginal effects (AME) were computed. According to Table 4, the average marginal effect varies between 1.1. and 2.1 percentage points. For example, for the twelve-month period, a change of Trigger 2 from zero to one changes the probability that the dependent variable takes the value one by 2.1 percentage points, keeping the remaining variables constant, i.e., if an observation accomplishes Trigger 2, the probability of being marked as an NPE is 0.021 higher, *ceteris paribus*. Such results show us that these factors do not have a great impact on the left-hand side variable.

To test the goodness of fit of our model, two measures were used. Firstly, it was computed the McFadden's pseudo-R^2 coefficient for each specification, calculated as:

$$McFadden's\ Pseudo - R^2 = 1 - \frac{L_1}{L_0},$$

where $L_1$ is the log likelihood of the estimated model and $L_0$ is the log likelihood of a null model that includes a constant term. As can be seen in Table 3, the pseudo-R^2 coefficient is slightly bigger than zero, which in a linear probability model would probably mean that our independent variables are not able to predict much of our dependent variable and, therefore, the model would not be statistically significant. However, the pseudo-R^2 measure in logistic regression models tends to be very low and it is difficult to interpret as we are trying to predict the outcome and the model only gives us the probability of the outcome. As such, the Receiver Operating Characteristic (ROC) curve was used as a second measure to evaluate the model's goodness of fit. The ROC curve tells us that the area under the curve should be greater than 0.5 and close to 1; if the area under the curve was 0.5, then our model would not be a strong predictor since it would be like a coin toss; if it was 1, then the model would be perfect in identifying the clients classified as NPE. Through table 5 it is possible to conclude that the area under the ROC curve increases as we increase our time horizon. For example, considering a two-month period, the area under the curve would be 0.55 whereas, in a twelve-month period analysis, it would be 0.66, approximately, therefore, our model would fit best for longer periods rather than short ones.

## 5. Conclusion

This paper aims to test the model BCP is trying to implement to identify and manage potential non-performing clients at a very early stage. At a preliminary statistical analysis, it can be observed that as time span increases, results show more significance: under a twelve-month period, the model can detect 40% of the clients classified with a non-performing exposure in 2018, in comparison with a 15% probability for a two-month time horizon. Despite the overall probability of detecting an NPE client being higher, one should bear in mind that 60% of the cases classified as an NPE in 2018 would not be detected by the model considering the previous year's evolution of the economic and financial conditions. Since it was not clear how useful are the variables incorporated in the model in predicting NPEs, a logit model was used to estimate the probabilities of being an NPE over the next period following Campbell's (2008) procedure.

Campbell (2008) and his predecessors tried to predict bankruptcy using logistic regressions. Since a client being classified as an NPE can be considered as a proxy for predicting bankruptcy, the same methodology was used to test our model. The results show that all explanatory variables have a positive coefficient and are statistically significant at a 5% significance level for all the periods under analysis, apart from the two-month horizon in which trigger 4 is not statistically significant. In addition to this, as the time horizon increases, each trigger presents a higher average marginal effect over the dependent variable. Nevertheless, and despite increasing as we broaden our time horizon, the area under the ROC curve does not have high values, which might indicate that some adjustments should be made in order to improve the model's fitness.

To improve the model's fitness, four measures are proposed. Firstly, the model could be more reliable if the remaining triggers were included since it would detect more clients at an early stage. Secondly, since we are analysing clients' economical and financial conditions, the model could have improved results if the time horizon was extended. In addition to this, and given this is a dynamic model, a sensitivity analysis regarding the triggers' mensuration could increase the effectiveness of the model. For example, changing the credit rating variation (trigger 1) from 2 to 1 would increase the probability of detecting an NPE client to 46.5%. Lastly, the model could include a trigger which would take into account the evolution of the industry the client is inserted in and, therefore, help building a future credit policy.

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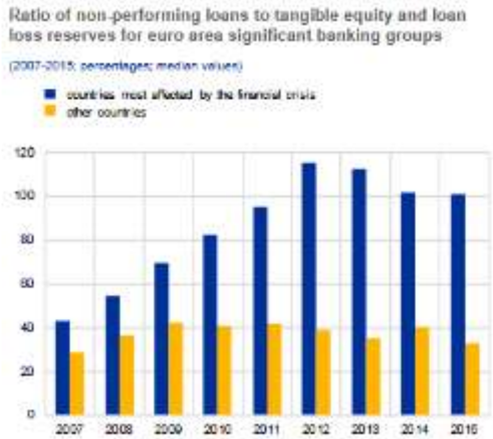
## 7. Appendix

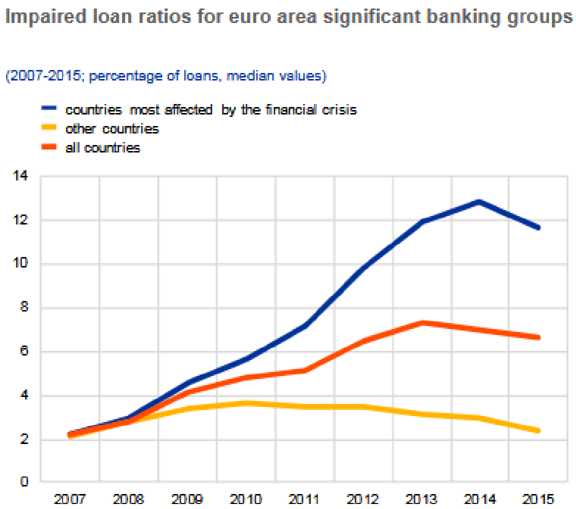
**Graph 1**

This graph presents the evolution of the Texas ratio[7] for the euro area significant banking groups, distinguishing it by countries most affected by the financial crisis and other countries.




**Graph 2**

This graph reports the impaired loan ratios for the euro area significant banking groups, dividing it in three groups: countries most affected by the financial crisis, other countries and all countries.




[7] Non-performing loans/ Tangible equity and loan loss reserves

## Table 1

## Summary Statistics

This table presents how many times each trigger and at least one trigger was activated, in absolute and in relative terms, for the entire data set, the clients classified as NPE in 20018 and the clients that are not classified as NPE.

| Panel A: Entire data set | | | | | | |
|---|---|---|---|---|---|---|
| *Section 1* | | | | | | |
| *# of months* | *trigger 1* | *trigger 2* | *trigger 4* | *trigger 5* | *trigger activated* | *# of clients* |
| 2 | 1 237 | 733 | 294 | 115 | 2 308 | 53 082 |
| 3 | 1 295 | 570 | 286 | 148 | 2 206 | 52 575 |
| 6 | 2 581 | 495 | 399 | 212 | 3 511 | 51 069 |
| 12 | 3 304 | 463 | 581 | 258 | 4 250 | 49 407 |
| *Section 2* | | | | | | |
| *# of months* | *% trigger 1* | *% of trigger 2* | *% of trigger 4* | *% of trigger 5* | *% of triggers activated per client* | |
| 2 | 2,3% | 1,4% | 0,6% | 0,2% | 4,3% | |
| 3 | 2,5% | 1,1% | 0,5% | 0,3% | 4,2% | |
| 6 | 5,1% | 1,0% | 0,8% | 0,4% | 6,9% | |
| 12 | 6,7% | 0,9% | 1,2% | 0,5% | 8,6% | |
| **Panel B: Clients classified as NPE in 2018** | | | | | | |
| *Section 1* | | | | | | |
| *# of months* | *trigger 1* | *trigger 2* | *trigger 4* | *trigger 5* | *trigger activated* | *# of clients* |
| 2 | 34 | 28 | 6 | 7 | 73 | 480 |
| 3 | 48 | 33 | 10 | 6 | 93 | 485 |
| 6 | 90 | 33 | 21 | 12 | 141 | 477 |
| 12 | 128 | 48 | 38 | 14 | 193 | 484 |
| *Section 2* | | | | | | |
| *# of months* | *% trigger 1* | *% of trigger 2* | *% of trigger 4* | *% of trigger 5* | *% of triggers activated per client* | |
| 2 | 7,1% | 5,8% | 1,3% | 1,5% | 15,2% | |
| 3 | 9,9% | 6,8% | 2,1% | 1,2% | 19,2% | |
| 6 | 18,9% | 6,9% | 4,4% | 2,5% | 29,6% | |
| 12 | 26,4% | 9,9% | 7,9% | 2,9% | 39,9% | |
| **Panel C: Clients non NPE** | | | | | | |
| *Section 1* | | | | | | |
| *# of months* | *trigger 1* | *trigger 2* | *trigger 4* | *trigger 5* | *trigger activated* | *# of clients* |
| 2 | 1 203 | 705 | 288 | 108 | 2 235 | 52 602 |
| 3 | 1 247 | 537 | 276 | 142 | 2 113 | 52 090 |
| 6 | 2 491 | 462 | 378 | 200 | 3 370 | 50 592 |
| 12 | 3 176 | 415 | 543 | 244 | 4 057 | 48 923 |
| *Section 2* | | | | | | |
| *# of months* | *% trigger 1* | *% of trigger 2* | *% of trigger 4* | *% of trigger 5* | *% of triggers activated per client* | |
| 2 | 2,3% | 1,3% | 0,5% | 0,2% | 4,2% | |
| 3 | 2,4% | 1,0% | 0,5% | 0,3% | 4,1% | |
| 6 | 4,9% | 0,9% | 0,7% | 0,4% | 6,7% | |
| 12 | 6,5% | 0,8% | 1,1% | 0,5% | 8,3% | |

## Table 2

## Probability of an NPE relative to a non NPE

This table gives us how higher is the probability of an NPE verify one of the triggers than a non NPE.

| Clients classified as NPE in 2018 / Clients non NPE | | | | | |
|---|---|---|---|---|---|
| *# of months* | *trigger 1* | *trigger 2* | *trigger 4* | *trigger 5* | *trigger activated* |
| 2 | 3,10 | 4,35 | 2,28 | 7,10 | 3,58 |
| 3 | 4,13 | 6,60 | 3,89 | 4,54 | 4,73 |
| 6 | 3,83 | 7,58 | 5,89 | 6,36 | 4,44 |
| 12 | 4,07 | 11,69 | 7,07 | 5,80 | 4,81 |

## Table 3

## Logistic regressions results

This table reports the results from the logistic regressions of our model for different time horizons: two, three, six and twelve months. The dependent variable is NPE and the absolute value of the z-statistic is shown in parenthesis. Furthermore, it presents the tests regarding the significance of the model at a 5% significance level. *denotes significant at a 5% level

| | 2 Months | | 3 months | 6 months | 12 months |
|---|---|---|---|---|---|
| Independent Variables | Model I | Model II | Model I | Model I | Model I |
| *Trigger 1* | 1,18<br>(6,52)* | 1,19<br>(6,60)* | 1,43<br>(9,07)* | 1,42<br>(11,73)* | 1,46<br>(13,40)* |
| *Trigger 2* | 1,51<br>(7,55)* | 1,52<br>(7,64)* | 1,85<br>(9,76)* | 1,93<br>(10,03)* | 2,21<br>(12,91)* |
| *Trigger 4* | 0,52<br>(1,23) | | 0,80<br>(2,34)* | 1,19<br>(4,90)* | 1,19<br>(6,21)* |
| *Trigger 5* | 1,90<br>(4,79)* | 1,91<br>(4,81)* | 1,31<br>(3,06)* | 1,73<br>(5,58)* | 1,43<br>(4,88)* |
| *Constant* | -4,81<br>(-97,44)* | -4,81<br>(-97,60)* | -4,83<br>(-97,05)* | -4,91<br>(-92,53)* | -4,96<br>(-89,67)* |
| *Observations* | 53082 | 53082 | 52575 | 51069 | 49407 |
| *NPEs* | 480 | 480 | 485 | 477 | 484 |
| *Pseudo-R^2* | 0,016 | 0,0157 | 0,026 | 0,0426 | 0,0669 |
| *LR test* | | | | | |
| *LR chi2 (1)* | 1,31 | | 4,5 | 18,34 | 30,55 |
| *Prob > chi2* | 0,2525 | | 0,034 | 0 | 0 |

## Table 4

### Average Marginal Effects

This table gives us the average marginal effect that each trigger has on the dependent variable, keeping the remaining variables constant. Only the models that were concluded to be statistically significant through the likelihood ratio test are presented.

| | 2 Months | 3 months | 6 months | 12 months |
|---|---|---|---|---|
| Independent Variables | Model II | Model I | Model I | Model I |
| *Trigger 1* | 0,011 | 0,013 | 0,013 | 0,014 |
| *Trigger 2* | 0,014 | 0,017 | 0,018 | 0,021 |
| *Trigger 4* | | 0,007 | 0,011 | 0,011 |
| *Trigger 5* | 0,017 | 0,012 | 0,016 | 0,014 |

## Table 5

This table shows the area under the ROC curve for the interval periods considered.

| ROC CURVE | Area under the curve |
|---|---|
| *2 months* | 0,55 |
| *3 months* | 0,58 |
| *6 months* | 0,62 |
| *12 months* | 0,66 |